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A novel approach for voltage secure operation using Probabilistic Neural Network in transmission network

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Abstract

This work proposes a unique approach for improving voltage stability limit using a Probabilistic Neural Network (PNN) classifier that gives corrective controls available in the system in the scenario of contingencies. The sensitivity of system is analyzed to identify weak buses with ENVCI evaluation approaching zero. The input to the classifier, termed as voltage stability enhancing neural network (VSENN) classifier, for training are line flows and bus voltages near the notch point of the *P–V* curve and the output of the VSENN is a control variable. For various contingencies the control action that improves the voltage profile as well as stability index is identified and trained accordingly. The trained VSENN is finally tested for its robustness to improve load margin and ENVCI as well, apart from trained set of operating condition of the system along with contingencies. The proposed approach is verified in IEEE 39-bus test system.

Keywords: VSENN; ENVCI; PNN; PMU

1. Introduction

The continuous increase in demand of load, limited scope for the expansion of existing conventional generation systems as well as transmission network, modern power systems operate under stressed condition. To this, further load increase and any contingency leads to point of concern for voltage stability (Kundur, 1994). Improper coordination between continuous and discrete controls, insufficient supply of reactive power in terms of size improper planning and location as well as been found to be the reason behind voltage deteriorations (Cutsem and Vournas, 1998). Voltage stability problem can be avoided by VAR placement (Thukaram and Lomi, 2000). For optimal placement and optimal value of VAR planning is done (Minguez et al., 2007). For on-line detection of voltage instability index, a new voltage

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stability index termed as equivalent node voltage collapse index (Wang et al., 2009). The work is emphasized on the design of VSENN classifier based on PNN (Mishra et al., 2008; Tripathy and Behera, 2012). After suitable training of the VSENN, the testing of the same is carried out for various contingencies. Studies carried out when contingencies occur with the system operating very near its voltage stability limit. The results obtained from using the test data of IEEE 39-Bus New England power system (Mishra et al., 2007).

The paper is organized in the following manner. Section 2 describes the sensitivity analysis and Section 3 focuses on the design of VSENN classifier. Section 4 gives the algorithm steps for simulation. Section 5 presents the simulation results and accordingly comparison of the results obtained with as well as without the proposed VSENN. Section 6 explains conclusion.

2. Sensitivity analysis

Even though the conventional methods which rely on actual power flow solution and state estimation of the system are more accurate, still the index evaluation is preferred for their obvious advantages of accuracy, fast calculation and less computation and potential for online applications. The reasons for using ENVCI are enumerated below. ENVCI takes into account the effect of the system external to the bus at which it is evaluated. It avoids the use of continuation method for estimating voltage stability margin. It can be a good index for online control application in large systems where voltage phasor information may be brought with the help of phasor measuring units (PMUs). The equivalent system model is shown in Fig. 1.

The ENVCI values at any bus can be determined by using the following equation,

$$\mathrm{ENVCI} = 2(e_k e_n + f_k f_n) - (e_k^2 + e_n^2) \tag{1}$$

where $\bar{E}_k = e_k + if_k$ and $V_n = e_n + if_n$.

V_n is the voltage of the Nth node. $\vec{E}_k$ is the voltage of the external system. It is to be noted that the ENVCI value of any weak bus lies close to *zero*, and that of a strong bus is close to *one*. The details can be referred from Wang et al. (2009).

3. Methodology adopted for designing the VSENN classifier

The PNN is a class of radial basis function (RBF) network (Specht, 1990), which follows supervised learning. As depicted in Fig. 2, the PNN in its structure consists of a radial basis layer and a competitive layer. Each set of input–output data are trained and classified by their distribution values as probability density function (PDF) expressed in Eq. (2). The input layer consists of S nodes to accept input feature vector (I). As mentioned in Eq. (2) the hth element of the middle layer Hd_h can be evaluated by the Euclidian distance between the ith input feature, I_i and the initialized weight (W_{ih}) connecting I_i to Hd_h.

$$Hd_h = \exp\left(-\frac{||W_{ih} - I||b^2}{\sigma^2}\right) \tag{2}$$

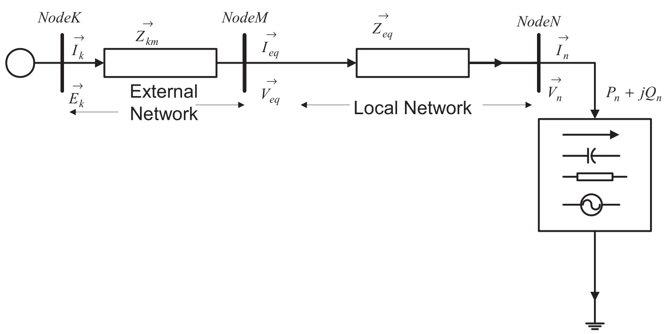

Fig. 1. Equivalent system model.

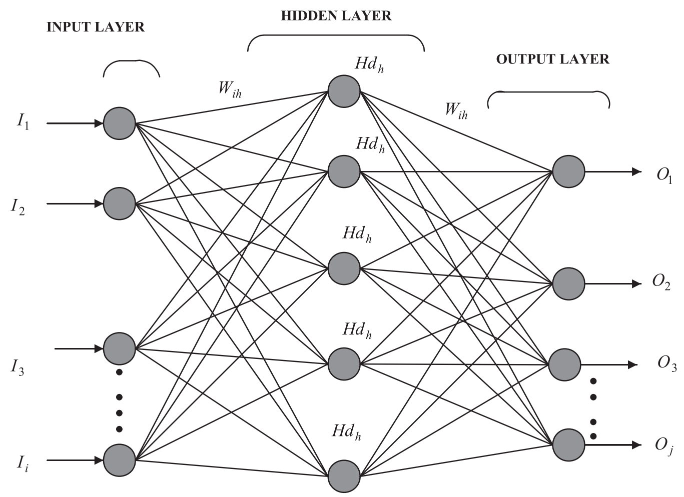

Fig. 2. PNN architecture.

where $||W_{ih} - I|| = \sum_{i=1}^{N_i}(I_i - W_{ih})^2$, assuming there are N_i number of input features in *I.b* is known as the *bias* which adjusts the sensitivity of radial basis neuron, and σ is the *spread* factor. Similarly, with the help of weights W_{hj} between the *h*th element of the hidden layer and *j*th element of output layer O_j, the output layer elements can be determined as shown in Eq. (3).

$$O_j = \frac{1}{N_j}\sum_{j=1}^{N_J} W_{hj} Hd_h \tag{3}$$

Among other networks for the purpose of classification, PNN offers better ability of rapid training with easier data handling and training. Moreover since the training algorithm is not iterative in nature, PNN has good potential to classify very fast, when more number of training sets are available. It has the following key features in it that makes it a good choice for problems of classification.

(i) Its implementation is based on probabilistic model of Bayesian classifiers.
(ii) There is no requirement of initializing the weights of the network.
(iii) The chances of convergence of the Bayesian classifier in PNN is almost certain, if sufficient numbers of training data sets are available.
(iv) The learning and recalling processes are independent of each other.
(v) The weight modification is not based on the difference between the inference and target vectors.

The next section discusses the detail methodology undertaken for designing the PNN classifier based controller.

4. Algorithm steps

The algorithm steps are given below which as follows:

Step-1 Input data to the system
Step-2 Increase load gradually in one bus for a time in steps of 2%.
Step-3 Check the sensitivity of each load bus with ENVCI values.
Step-4 Increase load till the point of collapse is reached. In addition to that a contingency is carried out.
Repeat the above steps for the other load buses and some various contingencies.
Step-5 All the data (voltage and line flows) are fed to the NN training set.

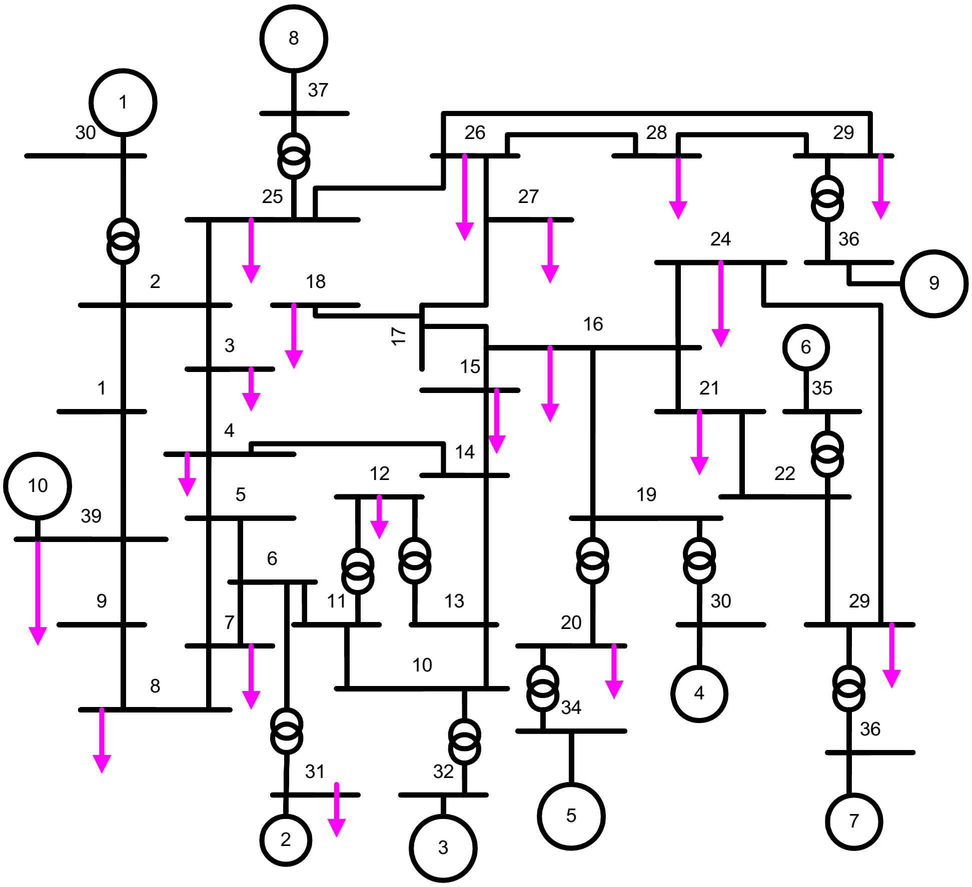

Fig. 3. IEEE-39 bus structure.

Step-6 The control action (output) for each of the disturbances, improves ENVCI is studied
Step-7 The VSENN is then trained with the help of large number of input and output data sets, using PNN.
Step-8 VSENN is tested in terms of its ability to take a corrective control action for any contingency which is not used for training purpose.

Table 1
VSENN classifier suggestion for control types to the 12 contingencies.

Contingencies (active and reactive power increase in load bus with line outage)	*P* increase	*Q* increase	Control type
At load bus 26 with LO 3-4	50%	145%	Increase voltage by 12% at 9th generator bus
At load bus 18 with LO 23-24	65%	82%	Decrease load shedding by 25% at 16th bus
At load bus 26 with LO 15-16	145%	45%	Decrease load shedding by 64.1% at 12th bus
At load bus 21 with LO 16-17	115%	45%	Decrease transformer tap by 10% at 10-32 bus
At load bus 16 with LO 15-16	50%	140%	Increase load shedding by 1% at 12th bus
At load bus 12 and LO 19-33	45%	145%	Decrease load shedding by 11% at 12th bus
At load bus 4 with LO 2-3	0%	10%	Decrease load shedding by 10% at 13th bus
At load bus 23 with LO 2-3	0%	10%	Increase real power generation by 13% in 1st gen.
At load bus 15 with LO 13-14	15%	2%	Increase the transformer tap by 6.61% at 12-13th bus
At load bus 20 with LO 13-14	0%	0%	Decrease load shedding by 11% at 12th bus
At load bus 23 with LO 10-11	2.8%	2.3%	Decrease Transformer tap by 7.9% at 29-38 bus
At load bus 25 with LO 10-13	1%	2%	Increase load shedding by 21% at 12th bus

Table 2
Voltage values and the ENVCI values obtained in twelve cases.

Test cases	Maximum voltage		Minimum voltage		ENVCI	
	Without control	With control	Without control	With control	Without control	With control
Case 1	1.04	1.02	0.8	0.97	0.067	0.176
Case 2	1.04	0.97	0.5	0.82	0.084	0.202
Case 3	1.5	1.14	0.5	0.83	0.187	0.250
Case 4	1.26	1.19	0.6	0.7	0.211	0.267
Case 5	1.5	1.17	0.8	1.01	0.835	0.951
Case 6	1.5	1.15	0.5	0.8	0.208	0.569
Case 7	1.5	1.35	1.0	0.9	0.276	0.593
Case 8	1.5	1.05	0.4	0.94	0.318	0.852
Case 9	1.1	1.17	0.5	0.93	0.764	0.795
Case 10	1.3	1.09	0.5	0.93	0.585	0.003
Case 11	0.9	1.06	0.5	0.62	0.137	0.212
Case 12	1.5	1.14	0.5	0.83	0.606	0.804

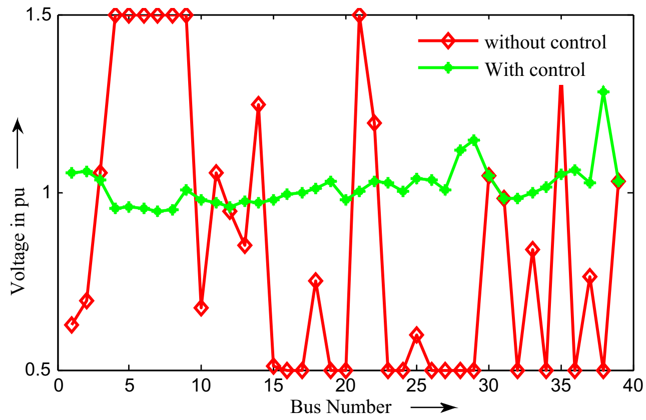

Fig. 4. System bus voltage profile for Case 1.

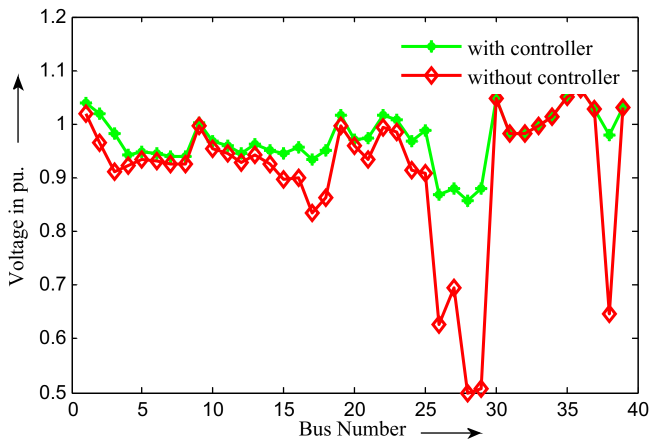

Fig. 5. System bus voltage profile for Case 2.

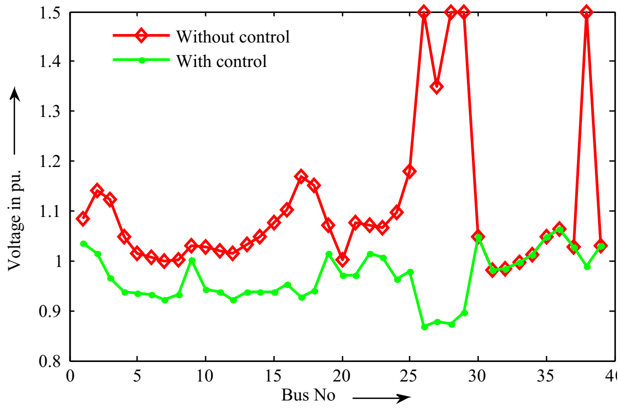

Fig. 6. System bus voltage profile for Case 3.

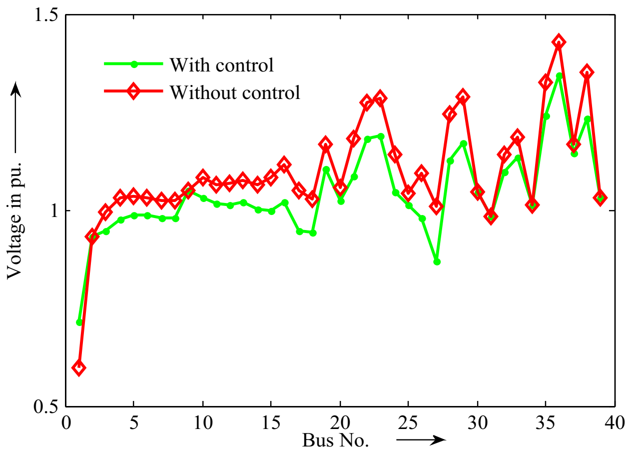

Fig. 7. System bus voltage profile for Case 4.

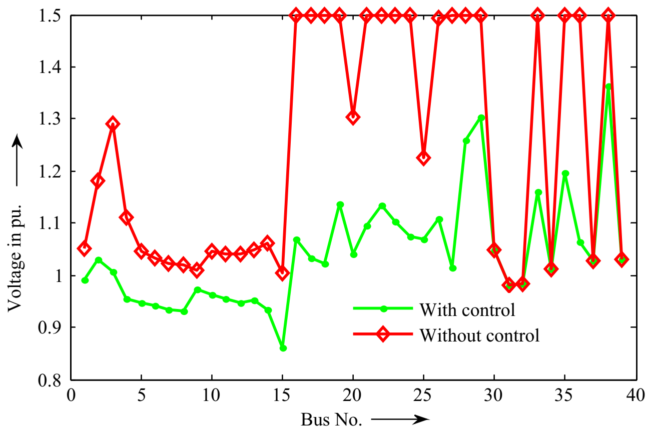

Fig. 8. System bus voltage profile for Case 5.

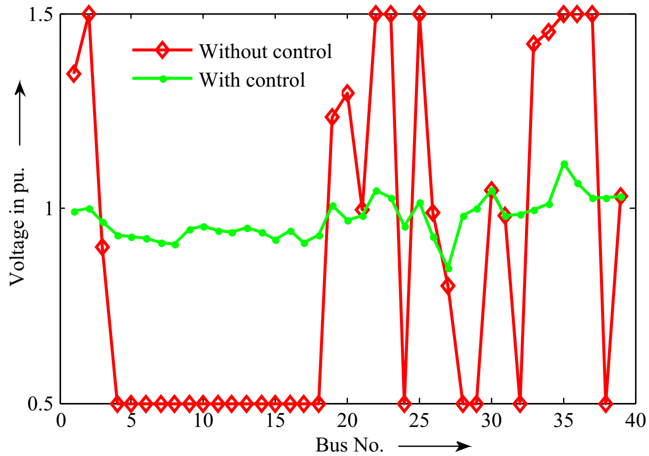

Fig. 9. System bus voltage profile for Case 6.

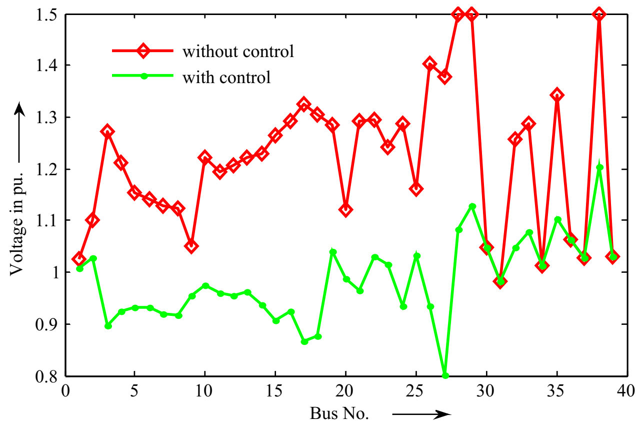

Fig. 10. System bus voltage profile for Case 7.

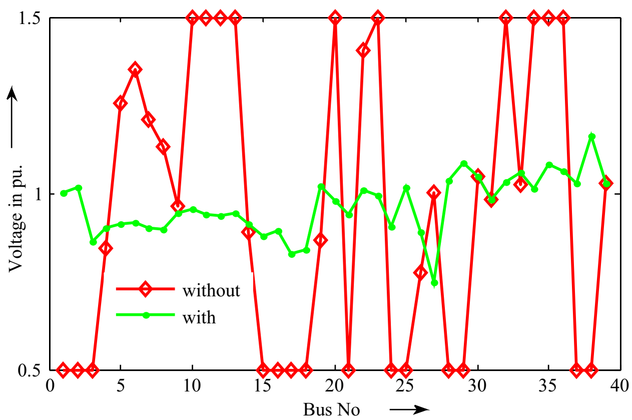

Fig. 11. System bus voltage profile for Case 8.

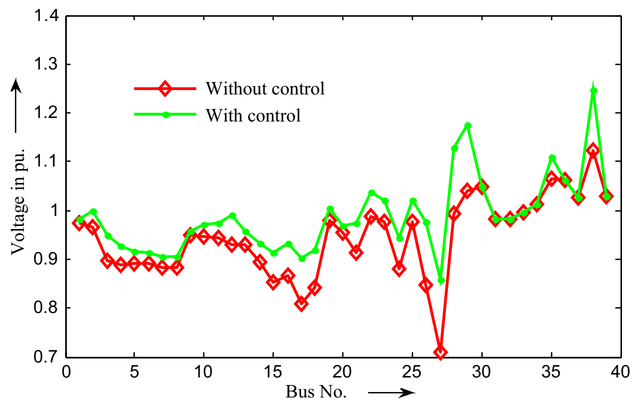

Fig. 12. System bus voltage profile for Case 9.

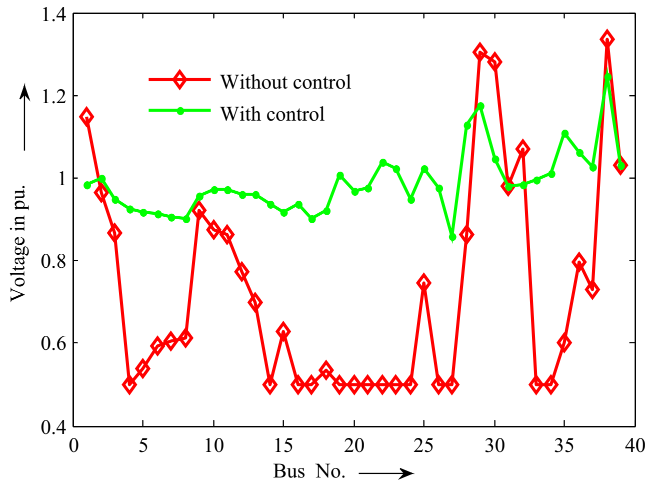

Fig. 13. System bus voltage profile for Case 10.

5. Simulation and results

The simulation is carried on IEEE-39 bus New England system. The system has 10 generators, 12 transformers, and 46 transmission lines shown in Fig. 3. The proposed method is simulated using Matlab® 7.0 software in dual core processor 2.2 GHz, and 4 GB RAM. 30 system topologies are considered by increasing the load in 2% step load increase in the range of 100–145% of nominal load shared by the generators equally. There are 32 single line outage (out of the total number of 46 lines) contingencies along with load increase in 16 load buses are simulated with $32 \times 16 \times 30 = 15{,}360$ patterns to achieve different scenarios. 15,360 patterns are generated from 30 system topology. Out of which 1564 scenarios gave invalid ENVCI result, several contingencies are created in order to test the designed classifier of control actions. Similar interpretations can be drawn for other line outages on the basis of system operational limit violations.

The control actions are related with active or reactive power re-scheduling, reactive power compensation and load shedding in dangerous situations. The sensitivity analysis is based on ENVCI assessing these critical areas, it measures the activity of the static variables of the system and it is computed with less computational effort. The VSENN classifier suggestion for control types to the 12 contingencies are illustrated in Table 1. The voltages obtained before and after taking the control actions in all cases are also enumerated in Table 2. Comparison is made with and without the VSENN controller in all the contingencies cases. The comparisons between the voltage profiles in all the buses with and without

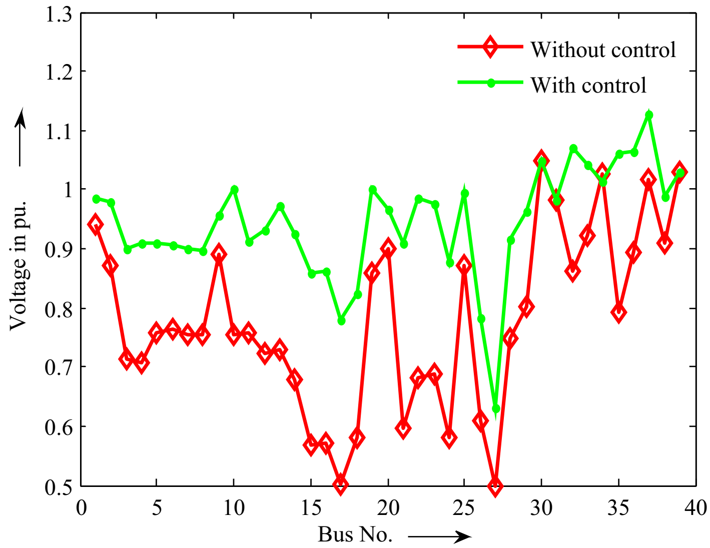

Fig. 14. System bus voltage profile for Case 11.

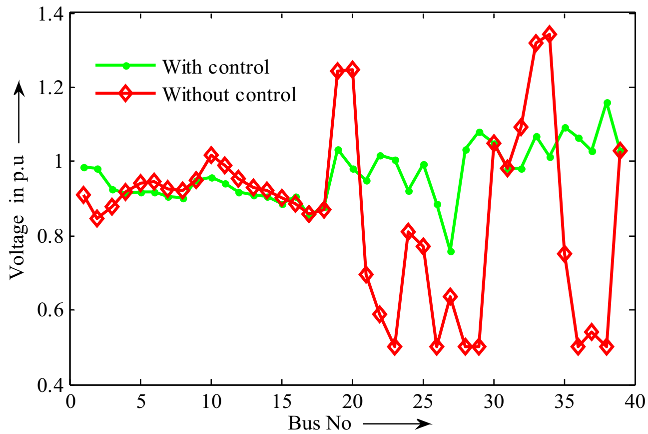

Fig. 15. System bus voltage profiles for Case 12.

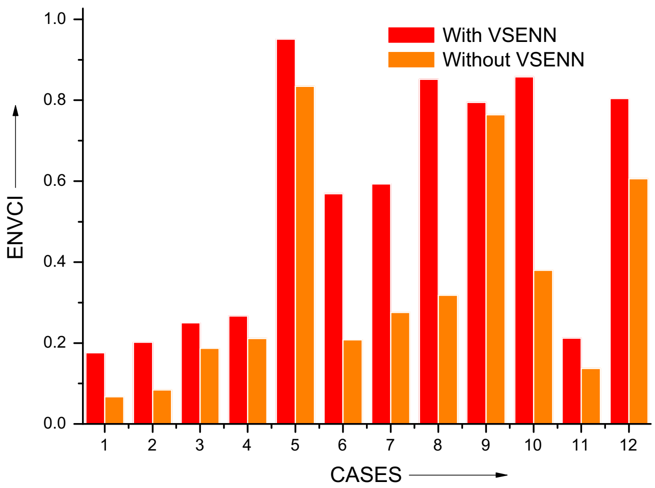

Fig. 16. ENVCI with and without the controller.

controller are shown in Figs. 4–15. The ENVCIs also compared for both with the controller and without the controller compared as shown in Fig. 16.

6. Conclusion

This work proposes VSENN for its application in load dispatch/control centres to facilitate fast control decisions, as well as sensing the weakness of the system by ENVCI. VSENN is tested for contingencies and the effect of this control action on system bus voltage profiles is verified. Voltage instability state is avoided by taking the control action suggested by VSENN. The voltage profiles improve by 7–36% from maximum limit, with the control and 7–54% for the minimum voltage limit respectively. Similarly the ENVCI also increased by 11–58% from the point of instability.

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